Ubiquitous Healthcare by Using Active Monitoring and Edge Computing

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Abstract. Ubiquitous healthcare is the mean to provide the whole-people anytime health monitoring and care by using information and communication technologies. How to reduce the deployment and operation cost while keep the care flow in real time manner is a challenge for the service providers. In this paper, a mechanism to perform multi-tiered cloud-based healthcare is proposed. This strategy has benefit both on time and transmission cost efficiency. By conducting the simulation under various service models, the results reveal significant improvement can be achieved on channel bandwidth and transmission time, which brings the guaranteed quality of service for people who need to accept the healthcare service.

Introduction

Healthcare is one of the world’s largest industries. The healthcare industry historically has lagged behind other industries in the adoption of information and communication technologies partially due to healthcare managers and executives struggling to cope with environmental challenges in the healthcare industry [1]. Nowadays, healthcare industry leaders and decision makers have begun to realize the supporting role of technology in their effort to maintain a focus on quality care while meeting the pressures from regulatory bodies, competition, and achieving business and performance goals. The mobile workstation, which can be used for medical records, diagnostics, charting, pharmacy, admissions, and billing, is an example of recently adopted technologies in hospitals [2]. Ubiquitous healthcare has become possible with rapid advances in information and communication technologies [3]. Ubiquitous healthcare will bring about an increased accessibility to healthcare providers, more efficient tasks and processes, and a higher quality of healthcare services. Ubiquitous healthcare is an emerging field of technology that uses a large number of environment and patient sensors and actuators to monitor and improve patients’ physical and mental condition. Tiny sensors are being designed to gather information on bodily conditions such as temperature, heart rate, blood pressure, blood and urine chemical levels, breathing rate and volume, activity levels, and almost any other physiological characteristic that provides information that can be used to diagnose health problems. In a cloud-based healthcare system, the data collected by these Internet-of-things (IoT) components are then transmitted to the cloud core to make decisions to provide the care process for the patients [4][5].

Related Technologies

Active Monitoring

There are various approaches to monitoring the condition about the patients. The two common approaches are the passive and active approaches. Both have their values and should be regarded as complementary, in fact they can be used in conjunction with one another. Both approaches monitor the patients by utilizing wearable or near-body devices. The passive approach uses devices to measure and record the patients’ status and the status are transformed to numerical data [6]. Then these data are sent to the cloud side in a manner controlled by the patients. These recording devices can be special purpose devices such as a wireless blood pressure meter, or they can be built into other devices
such as watches or glasses. These devices communicate each other and exchange information with body or home gateway by Bluetooth protocol in general. The passive monitoring approach doesn’t poll the measuring devices periodically and information collected to evaluate the patients’ status are delivered by the patients. Since the measurement is always kept in non-continuous form then the bandwidth resource used by this approach is very low. On the other hand, the active approach uses the polling form to collect the patients’ data and issues alarms to the patients to guide the care process. It will generate more message transmission especially if advanced analysis or trying to retrieve more information from the patients depends on different patients’ condition. The extra message overhead comes from the following scenarios: (1) When the patient doesn’t return the physiological parameters on time; (2) When system deems it’s necessary to intervene to provide guidance for the patients; (3) When system ask the patients to provide more information to help the system to construct the models. The active approach provides explicit control on the generation of extra messages. Given the complementarity of the two mechanisms, we need to explore ways to get the best of both worlds. A possibility is to perform the adaptive active measurement probing to the patients depending on the attribute of different disease and recovery type or change the active probing threshold in the probing mechanism. When the active measurement is completed then the appropriate passive measurements can be paused thus reducing the gathering of unnecessary data. By comparing and contrasting the active and passive measurements, the co-validity of the different measurements can be verified, and much more detailed information on carefully specified/scheduled phenomena are made available.

**Edge Computing**

Edge computing is a method of optimizing cloud computing systems by performing data processing at the edge of the network, near the source of the data. This reduces the communications bandwidth needed between sensors and the central data center by performing analytics and knowledge generation at or near the source of the data [7]. This approach requires leveraging resources that may not be continuously connected to a network such as laptops, smartphones, tablets and sensors. Edge computing covers a wide range of technologies including wireless sensor networks, mobile data acquisition, mobile signature analysis, cooperative distributed peer-to-peer ad hoc networking and processing also classifiable as local cloud/fog computing and grid/mesh computing, dew computing, mobile edge computing, cloudlet, distributed data storage and retrieval, autonomic self-healing networks, remote cloud services, augmented reality, and more. Edge computing pushes applications, data and computing power (services) away from centralized points to the logical extremes of a network. Edge computing replicates fragments of information across distributed networks of web servers, which may spread over a vast area [8]. To ensure acceptable performance of widely dispersed distributed services, large organizations typically implement edge computing by deploying Web server farms with clustering. Edge computing has utilized technology advances and cost reductions for large-scale implementations have made the technology available to small and medium-sized businesses. The ubiquitous healthcare can be achieved by this cloud-edge-end architecture in cost-effective way [9] [10].

**Proposed System Architecture**

The cloud-edge-end architecture considered in this paper is depicted in Figure 1. The end nodes collect the bio-signal data and transmitted to the edge nodes. These data are then processed the edge nodes to the cloud server. Initially, the system is operated in the general model. That is, all the data collected by the end nodes are transmitted to the edge nodes, then bypassed to cloud server to maintain the complete data set to build the classification or prediction model. Once the model is constructed by the decision core implemented in the server after enough amount of data are collected to the server or the built model achieves significant accuracy, the system then switches to the slim model. The server then sends the activate message to the edge nodes, which contains the built model
and the satisfied condition. The model is then stored in the edge nodes for responding the decision result to the end devices.

Figure 1. Simulated scenario.

Active monitoring is implemented here by interactive model. That is, the information about the bio-signal parameters which will collect from the patients are determined based on the current status of patients. The interactive contents are determined by the recovery record and risk evaluation are provided by the clinical physicians and medical staffs, the knowledge database established from the domain experts, and the inference result generated by the decision core implemented in the cloud. From this manner, highly customized healthcare solutions can be made not only providing more appropriate care model for the patients but also bringing the feasible business models for the service providers.

The rule is generated by the cloud core by executing pre-determined machine learning techniques. In supervised learning, for example, the decision tree is implemented to determine the class of health or the recovery status of the patient, then next treatment process can be planned. As another example, artificial neural network also has great capability to predict the possible change of the patient status with numerical probability form to provide decision reference to the medical or care providers. In unsupervised learning schemes, the clustering can be adopted to group the patients to classify the expected risk if he/she has the same conditions or behavior. The ensemble method which combine multiple classifiers are also can be used frequently in imbalanced positive-negative class cases. The decision core can determine the proper strategy to implement by integrating all the considerations from management, efficiency and medical flow perspectives.

In summary, the edge nodes can be regarded as the first filter to reduce the information processing overhead of end nodes and the time transmission delays between the long journey between the end and cloud. It also possesses the benefit of information exchange between adjacent edge nodes when the coordinated care and support operations are activated. In such case, instructions to care the patients or interactions for different families are shared and the information retrieved from the cloud are dispatched to different end nodes in group manner. To ensure the availability in advance, edge node group can be assigned in each management zone. Once one of the edge node is crashed, other edge nodes can used as the backup nodes. The only necessity to carry out this mechanism is to install the same add-in software module to each edge node candidate device.

Experiments Study

Simulation Environment

Our experiments are conducted on a cloud comprised of 4 physical nodes cluster. Each node has a memory of 8 GB, 4 cores Intel i7-4820K CPU, and a disk storage of 2TB configured with RAID 1. Linux CentOS 6.5 operation system is installed on the cluster system and an additional master node is
used as NameNode and JobTracker. The Hadoop/Hive packages are also installed to simulate the continuous data streaming from the end nodes in our experiment. The Cloud server is used dedicatedly to the experiment during the performance evaluation to ensure the measurement results are truly reflected and recorded. The classification of patients included orthopedic rehabilitation patients, after-surgery orthopedics rehabilitation patients and patients with chronic diseases such as hypertension and diabetes. The information including diet, physical activity and exercise pattern, body weight, diastolic blood pressure, systolic blood pressure, blood glucose before meals and postprandial blood glucose levels are all uploaded to the cloud after daily measurements. The cloud will deliver customized care instructions, dietary guidelines, exercise guidelines, living and other guidelines and health education videos to patients' end devices after calculating the risk degree for the patients. The multiple-class logistic regression decision module is implemented in the cloud. The type of data contains the picture, video and text files according to the different needs of the patient. The different rate of input data stream is sent to the edge node, and then sent to the cloud. The rate of patient access to the system follows Poisson distribution and the patient type and postoperative recovery schedule are assigned in random manner.

**Evaluation Criteria**

The performance of the simulated system architecture can be evaluated by some parameters including response time, bandwidth reduction, active overhead and efficiency for different healthcare requirement. The response time is measured by averaging the turnaround time between the patient side and the cloud side. The bandwidth reduction is used to evaluate the saving of message number under the proposed system. The active overhead means the average extra messages required to satisfy different type of patients according to their current condition. Finally, the efficiency for different healthcare requirement can be examined by the fitting degree for the contents and recovery schedule for the patients. It is measured to justify the accuracy of the decision engine in our experiments. The transmitted contents and instructions are examined and verified by medical experts.

**Performance Study**

The result of average response time in 10000 times uploads is plotted in Table 1. The latency consists of transmission delay and processing delay in the edge node and in the cloud. In general, the requirement for orthopedic rehabilitation patients will decrease when the patients are well-recovered after a period of time. For patients with chronic diseases the message will remains the same amount. Thereafter, the overall response time is only slightly superior to non-edge situation due to the effect of mixed-type mixed-condition patients and active monitoring. The same result is also appeared in Table 2. Although the overall bandwidth savings have been reduced, the improvement have not been much significant due to the adoption of active supervision. However, it can be found if the upstream and downstream links are examined separately, the uplink bandwidth resources will be significantly reduced while most of the additional burden appears in the downlink part of the link.

<table>
<thead>
<tr>
<th>Implement type</th>
<th># Transmitted messages</th>
<th>Implement type</th>
<th>Average response time (Sec.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Edge</td>
<td>3292175</td>
<td>Edge</td>
<td>0.12</td>
</tr>
<tr>
<td>Non-edge</td>
<td>6976487</td>
<td>Non-edge</td>
<td>1.28</td>
</tr>
</tbody>
</table>

The result of active overhead shows that the average load is about 1.38 times (21.67MB / 15.7MB) of the original amount of messages. This is because the amount of data fed back to the end device in the active transfer is still not small, which cancel out the expected amount of reduction originally. It is obvious that this burden will be minimized if all the instructions and resources for health education are pre-stored on the end device. Finally, for the consistency of different types of care needs, we found
that 90.42% consistent degree is achieved after reviewing and summarizing the return information of 126 patients, which reflects the accuracy of the method for the prediction model selected by this system. Due to the fact that the sample size is not huge enough, there is room for improvement for the trained model in the generalization aspect.

**Conclusion**

This study attempts to discover the effect of remote healthcare under the environment of active monitoring and edge computing. We conducted the simulations to investigate the effects of different parameters for the target architecture in the out-of-hospital environment. The experimental results show that with the aid of the edge device, the patient will be brought to the benefit of instantaneous personal status transmission and personalized medical care services. To reach more practical conclusions, further research will include study on the diversity of patient types, the breadth of uploading data, and the design of transmission and filtering mechanisms.

**References**


